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Prediction of Field Sand Liquefaction Caused by Earthquake by Optimum Seeking Method

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SYNOPSIS: There are many uncertain factors influencing the field sand liquefaction induced by earthquake, therefore, the predictions of available methods are usually unsatisfactory. In this paper, a new way is developed, i.e., according to the available field sand liquefaction data, the influencing factors are optimized by optimum seeking method, then the prediction is made on the optimized results. By this method, 20 field cases are predicted and the correct rate is 95%. It proves that the suggested method is effective and feasible.

INTRODUCTION

Soil liquefaction induced by earthquake has made enormous damage to buildings, earth embankments and retaining structures. So, since the June 16, 1964 earthquake at Niigata and the Alaskan earthquake of 1964, extensive studies in liquefaction have been made by scholars and geotechnical engineers, and a lot of methods for predicting field sand liquefaction induced by earthquake have been developed (Seed, 1979, Finn, 1981, Seed et al., 1983). Basically, the existing liquefaction predicting methods can be grouped into the following categories:

(a) Geological method based on the superimposed map of the geologic map and the groundwater map (Youd and Bennett, 1983);

(b) Methods based on the evaluation of the cyclic stress (or strain) a proposed design earthquake would develop and comparison of these stresses (or Strains) with those observed to cause liquefaction in representative samples in an appropriate laboratory test;

(c) Empirical methods based on field observations of the performance of sand deposits during past earthquakes.

Because of the uncertainty of the factors influencing the liquefactions, none of the existing methods can claim to be completely accurate. In fact, when testing against case histories, they provide varying results. Furthermore, each method has its own disadvantages. For example, the first method is only an empirical qualitative one; the methods of the second category are based on the laboratory test results, but the experimental errors always exist; and most of the methods of the third category ignored some important influencing factors.

In this paper, a new way is developed, i.e., according to the available field sand liquefaction data, the influencing factors are optimized by optimum seeking method, then the prediction is made on the optimized results. This method can be simply and easily used and makes it possible to avoid theoretical assumptions and experimental errors.

OPTIMUM SEEKING METHOD

Optimization theory is a very important branch of Applied Mathematics and has a widespread application in the practical world. Generally, optimization techniques can, for convenience, be divided in two classes: direct (or experimental) and indirect (analytical) methods. Optimum seeking method is direct because it searches for an optimum directly rather than solving an equation. Optimum seeking method includes Climbing search, Fibonacci search, 0.618 (or Golden section) search, etc. (Beightler et al., 1979, Mital, 1976). In this paper, the Fibonacci search is used.

Fibonacci search was developed by an American scholar J.Kiefer in 1953. The Fibonacci numbers are

$$1, 1, 2, 3, 5, 8, 13, 21, 34, \dots$$

Using F_0, F_1, F_2, \dots to denote the numbers respectively, we can have

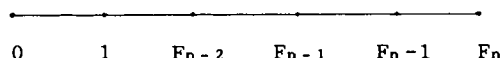
$$F_n = F_{n-1} + F_{n-2} \quad (n \geq 2)$$

Thus, given $F_0=F_1=1$, the infinite sequence of numbers F_2, F_3, \dots can be determined.

The Fibonacci search procedure for univariate case is as follows

(a) The number of all the experimental points equals F_{n-1}

If so, the first two experiments are placed at points F_{n-1} and F_{n-2} .



According to the experimental results, if the point F_{n-1} is better, the experimental points below F_{n-2} are omitted, if the point F_{n-2} is better, the experimental points above F_{n-1} are omitted. Then, the remained F_{n-1-1} experimental points are renumbered and one of the two points F_{n-2} and F_{n-3} is the remained better one and the other one is the new point to be experimented. As before, comparing the experimental results of the two points, the experimental interval is bisected in the worse point, and the shorter interval is omitted and the longer interval in which the better point lies remains. Now, there are only F_{n-2-1} points in the new experimental interval. Through further experimenting, we can obtain the best point finally.

(b) The number of all the experimental points is greater than F_{n-1} but smaller than F_{n+1-1}

In this case, we can assume some experimental points so that the number of all the experimental points equals F_{n+1-1} . We may assume these points arbitrarily so as to ensure the best point does not lie at any of these points. Then, the search may be carried out by the procedure introduced before.

For multivariate case, we can also use the procedure for univariate case. When one of the factors is optimized, the others are assumed to be constant.

SELECTION OF FIELD SAND LIQUEFACTION DATA

Theoretical researches and field investigations show that there are many factors influencing field sand liquefaction introduced by earthquake, such as relative density of soil, depth of sand and water table, earthquake magnitude, etc.. Every factor has

different level of influences on liquefaction behavior. According to the general principle of selecting influencing factors, i.e.

- 1) The major factors;
 - 2) The factors available to majority of field sand liquefaction data;
 - 3) The factors easy to obtain and determine.
- We select the following five factors:
- 1) Magnitude of the earthquake;
 - 2) Distance from the source of energy release;
 - 3) Depth of water table;
 - 4) Depth of sand;
 - 5) Average standard penetration test [SPT] blow count.

and divide grades according to Table 1.

Some of the cases where liquefaction has or has not occurred during an earthquake have been documented in the literature. The data used in this paper has been drawn from some typical reports (Seed et al., 1971, Liu Hui-xian, 1985) and includes a total of 40 data points corresponding to 13 earthquakes. These points contained cases where liquefaction did and did not occur. Included in these case histories are information on the soil and earthquake characteristics. As shown in Table 2, the influencing factors are graded on Table 1, for the liquefaction behavior, "0" stands for no liquefaction and "1" for liquefaction.

OPTIMUM SEEKING BY 21 SECTION METHOD

Using the former 20 data points in table 2, the five influencing factors are optimized. For this case, $F_n=21$ and the number of all the experimental points equals F_{n-1} . This case is a multivariate one and we must optimize the factors respectively.

(a) The magnitude is optimized: The other four factors are assumed to be constant, or each factor is multiplied by 13 ($F_{n-1}=13$). For every data point, the products are added together and the sums are denoted by $\Sigma 4$. The grades of magnitudes are multiplied by 8 ($F_{n-2}=8$) and the products are added to $\Sigma 4$ respectively, and the sums are denoted by $\Sigma 5$. According to $\Sigma 5$, every data point is graded and the grade is minused by the liquefaction behavior grade respectively. The absolute

Table 1. The Factor Grading Standard

Factors	Grades			
	0	1	2	3
Magnitude	≤ 5.9	6.0 - 6.9	7.0 - 7.9	≥ 8.0
Distance (Km)	≥ 101	100 - 46	45 - 11	≤ 10
Depth of water (m)	≥ 4.0	3.9 - 2.6	2.5 - 1.1	≤ 1.0
Depth of sand (m)	≥ 20.0	19.9 - 10.0	9.9 - 5.0	≤ 4.9
SPT Blow Count	≥ 20	19 - 11	10 - 6	≤ 5

Table 2. Field Sand Liquefaction Data

No.	Earthquake	Date	Site	Magnitude		Distance		Depth of Water		Depth of Sand		SPT Blow Count		Liquefaction Behavior	
				V. (A) Grade		V. (B) (Km) Grade		V. (C) (m) Grade		V. (D) (m) Grade		V. (E) Grade		Lique- faction	Grade
1	Niigata	1802	Niigata	6.6	1	39	2	1	3	6	2	6	2	No	0
2	Niigata	1887	Niigata	6.6	1	47	1	1	3	6	2	6	2	No	0
3	Fukui	1948	Takaya	7.2	2	6	3	1	3	7	2	28	0	No	0
4	Chile	1960	Puerto Montt	8.4	3	113	0	3.5	1	6	2	18	1	No	0
5	Niigata	1964	Niigata	7.5	2	52	1	3.5	1	8.5	2	7	2	No	0
6	Niigata	1964	Niigata	7.5	2	52	1	1	3	6	2	12	1	No	0
7	Tokachioki	1968	Hachinohe	7.8	2	172	0	1	3	3.5	3	14	1	No	0
8	Tokachioki	1968	Hachinohe	7.8	2	172	0	1.5	2	3	3	15	1	No	0
9	Mino Owari	1891	Ogaki	8.4	3	32	2	1	3	5	2	4	3	Yes	1
10	Mino Owari	1891	Ginan West	8.4	3	32	2	2	2	9	2	10	2	Yes	1
11	Santa Barbara	1925	Sheffield Dam	6.3	1	32	2	4.5	0	7.5	2	3	3	Yes	1
12	El Centro	1940	Brawley	7.0	2	8	3	4.5	0	4.5	3	9	2	Yes	1
13	Tohnankai	1944	Komei	8.3	3	161	0	1.5	2	4	3	4	3	Yes	1
14	Fukui	1948	Takaya	7.2	2	6	3	3.5	1	4	3	12	1	Yes	1
15	Chile	1960	Puerto Montt	8.4	3	113	0	3.5	1	4.5	3	6	2	Yes	1
16	Niigata	1964	Niigata	7.5	2	52	1	1	3	6	2	2		Yes	1
17	Alaska	1964	Snow River	8.3	3	97	1	0	3	6	2	3		Yes	1
18	Tokachioki	1968	Hachinohe	7.8	2	172	0	1	3	3.5	3	2		Yes	1
19	Haicheng	1975	Liao Chem. Plant	7.3	2	64	1	1.5	2	6.2	2	2		Yes	1
20	Tangshan	1976	Weige Village	7.8	2	42.5	1	1.35	2	2.3	3	1		Yes	1
21	Niigata	1802	Niigata	6.6	1	39	2	1	3	6	2	12	1	No	0
22	Niigata	1887	Niigata	6.1	1	47	1	1	3	6	2	12	1	No	0
23	Chile	1960	Kaosenpo	8.4	3	113	0	3.5	1	7	2	10	2	No	0
24	Haicheng	1975	Shuangtai Floodgate	7.3	2	59	1	1	3	8	2	20	0	No	0
25	Niigata	1964	Niigata	7.5	2	52	1	1	3	6	2	12	1	No	0
26	Niigata	1964	Niigata	7.5	2	52	1	3.5	1	7.5	2	6	2	No	0
27	Tokachioki	1968	Hachinohe	7.8	2	172	0	1.5	2	3.5	3	18	1	No	0
28	Mino Owari	1891	Ogase Pond	8.4	3	32	2	2.5	2	4	3	10	2	Yes	1
29	El Centro	1940	All Am. Canal	7.0	2	8	3	6	0	7.5	2	4	3	Yes	1
30	El Centro	1940	Solfatara Canal	7.0	2	8	3	1.5	2	6	2	1	3	Yes	1
31	Fukui	1948	Shonenji Temple	7.2	2	6	3	1	3	3	3	3	3	Yes	1
32	Chile	1960	Puerto Montt	8.4	3	113	0	3.5	1	4.5	3	8	2	Yes	1
33	Niigata	1964	Niigata	7.5	2	52	1	1	3	7.5	2	8	2	Yes	1
34	Niigata	1964	Niigata	7.5	2	52	1	1	3	6	2	7	2	Yes	1
35	Alaska	1964	Snow River	8.3	3	97	1	2.5	2	6	2	5	3	Yes	1
36	Alaska	1964	Scott Glacier	8.3	3	89	1	0	3	6	2	10	2	Yes	1
37	Alaska	1964	Valdez	8.3	3	56	1	1.5	2	6	2	13	1	Yes	1
38	Tokachioki	1968	Hakodate	7.8	2	283	0	1	3	4.5	3	6	2	Yes	1
39	Tangshan	1976	Longwang Temple	7.8	2	64	1	2.25	2	2.3	3	4	3	Yes	1
40	Tangshan	1976	Rujia Mine	7.8	2	25	2	1	3	7	2	4	3	Yes	1

value $\Sigma |D|$ of the subtrahends is 6; Then, the grades of magnitudes are multiplied by 13 and the products are added to $\Sigma 4$ respectively, and the new sums $\Sigma 5$ are obtained. According to $\Sigma 5$, every data point is graded and the new grade is minused by the liquefaction behavior grade respectively again. The new $\Sigma |D|$ is 5 smaller than 6 (Table 3). So we can consider point 13 is better than point 8. The experimental interval below point 8 is omitted and the points in the interval between point 13 and 21 are optimized again. The symmetrical point of 13 is 17, and the $\Sigma |D|$ for point 17 is smaller than $\Sigma |D|$ for point 13. So the best point is 17;

(b) Secondly, the grades of magnitudes are multiplied by 17. The grades of the depth of water table, the depth of sand and the SPT blow count are multiplied by 8 respectively. The distance is optimized and the best point is 8. By the same way, we can get the best points of the depth of water table, the depth of sand and the SPT blow count respectively. They are 5, 8 and 17. The $\Sigma |D|$ for these best points is 0. So the first turn of optimization is finished;

(c) The second turn of optimization: the grades of magnitudes are multiplied by 8, the

grades of the depths of water table by 5, the grades of the depths of sand by 8 and the grades of the SPT blow counts by 17, the magnitude is optimized again and the best point is also 17. The other four factors are optimized again and the results are also the same as above. So the whole optimization is finished. The final optimized results are shown in Table 4.

APPLICATION

By the optimized results, the later 20 data points are predicted (Table 5) and the correct rate is 95%. It proves that the suggested method is effective and feasible.

CONCLUSIONS

The method suggested in this paper is simple and practical, and makes it possible to avoid theoretical assumptions and experimental errors. The application of this method shows that it is effective and feasible.

It is worth mentioning that the suggested method also has a function of selecting

Table 3. The First Optimization of Magnitude

No.	(B)X13	(C)X13	(D)X13	(E)X13	$\Sigma 4$	(A)X8	$\Sigma 5$	Pre. Grade	Pra. Grade	$ D $	(A)X13	$\Sigma 5$	Pre. Grade	Pra. Grade	$ D $
1	26	39	26	26	117	8	125	1	0	1	13	130	1	0	1
2	13	39	26	26	104	8	112	1	0	1	13	117	0	0	0
3	39	39	26	0	104	16	120	1	0	1	26	130	1	0	1
4	0	13	26	13	52	24	76	0	0	0	39	91	0	0	0
5	13	13	26	26	78	16	94	0	0	0	26	104	0	0	0
6	13	39	26	13	91	16	107	1	0	1	26	117	0	0	0
7	0	39	39	13	91	16	107	1	0	1	26	117	0	0	0
8	0	26	39	13	78	16	94	0	0	0	26	104	0	0	0
9	26	39	26	39	130	24	154	1	1	0	39	169	1	1	0
10	26	26	26	26	104	24	128	1	1	0	39	143	1	1	0
11	26	0	26	39	91	8	99	0	1	1	13	104	0	1	1
12	39	0	39	26	104	16	120	1	1	0	26	130	1	1	0
13	0	26	39	39	104	24	128	1	1	0	39	143	1	1	0
14	39	13	39	13	104	16	120	1	1	0	26	130	1	1	0
15	0	13	39	26	78	24	102	1	1	0	39	117	0	1	1
16	13	39	26	26	104	16	120	1	1	0	26	130	1	1	0
17	13	39	26	26	104	24	128	1	1	0	39	143	1	1	0
18	0	39	39	26	104	16	120	1	1	0	26	130	1	1	0
19	13	26	26	26	91	16	107	1	1	0	26	117	0	1	1
20	26	39	26	39	140	16	156	1	1	0	26	166	1	1	0
Total										6					5

For (A)X8, when $\Sigma 5 < 102$, the Pre. Grade is 0, when $\Sigma 5 \geq 102$, the Pre. Grade is 1;
For (A)X13, When $\Sigma 5 < 130$, the Pre. Grade is 0, when $\Sigma 5 \geq 130$, the Pre. Grade is 1.

Notes: The Pre. Grade is the prediction grade and the Pra. Grade is the practical grade;
 $|D|$ is the absolute value of the subtrahend of the Pre. Grade and the Pra. Grade.

Table 4. The Final Optimization Result

No.	(A)X17	(B)X8	(C)X5	(D)X8	(E)X17	$\Sigma 5$	Prediction Grade	Practical Grade	D
1	17	16	15	16	34	98	0	0	0
2	17	8	15	16	34	90	0	0	0
3	34	24	15	16	0	89	0	0	0
4	51	0	5	16	17	89	0	0	0
5	34	8	5	16	34	97	0	0	0
6	34	8	15	16	17	90	0	0	0
7	34	0	15	24	17	90	0	0	0
8	34	0	10	24	17	85	0	0	0
9	51	16	15	16	51	149	1	1	0
10	51	16	10	16	34	127	1	1	0
11	17	16	0	16	51	100	1	1	0
12	34	24	0	24	34	116	1	1	0
13	51	0	10	24	51	136	1	1	0
14	34	24	5	24	17	104	1	1	0
15	51	0	5	24	34	114	1	1	0
16	34	8	15	16	34	107	1	1	0
17	51	8	15	16	51	141	1	1	0
18	34	0	15	24	34	107	1	1	0
19	34	8	10	16	34	102	1	1	0
20	34	16	10	24	17	101	1	1	0
Total									0
When $\Sigma 5 < 100$, the Prediction Grade is 0, when $\Sigma 5 \geq 100$, the Prediction Grade is 1.									

Table 5. The Prediction Result

No.	(A)X17	(B)X8	(C)X5	(D)X8	(E)X17	$\Sigma 5$	Prediction Grade	Practical Grade	D
21	17	16	15	16	17	81	0	0	0
22	17	8	15	16	17	72	0	0	0
23	51	0	5	16	34	106	1	0	1
24	34	8	15	16	0	73	0	0	0
25	34	8	15	16	17	90	0	0	0
26	34	8	5	16	34	97	0	0	0
27	34	0	10	24	17	85	0	0	0
28	51	16	10	24	34	135	1	1	0
29	34	24	0	16	51	125	1	1	0
30	34	24	10	16	51	135	1	1	0
31	34	24	15	24	51	148	1	1	0
32	51	0	5	24	34	114	1	1	0
33	34	8	15	16	34	107	1	1	0
34	34	8	15	16	34	107	1	1	0
35	51	8	10	16	51	136	1	1	0
36	51	8	15	16	34	124	1	1	0
37	51	8	10	16	17	102	1	1	0
38	34	0	15	24	34	107	1	1	0
39	34	8	10	24	51	127	1	1	0
40	34	16	15	16	51	132	1	1	0
Total									1

influencing factors. From the optimization result, we can see that the magnitude and the SPT blow count have the greatest influences, but the depth of water table has the smallest influence. With more field sand liquefaction data, we can choose more factors and appraise the influence level of every factor.

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